# Master Thesis

* Møde 31/01/2025

**The uncanny valley (UV) is a negative emotional reaction to artificial characters that look almost but not quite human. We have collected EEG data from 30 subjects on this topic, and we need a thorough analysis of the data using standard EEG analysis tools, to understand better how this phenomenon works.**

* + Spørgsmål:
    - Dataset?
    - Guide med metoder?
    - Uncanny Valley Paper
    - Inspirational Papers
    - Hvad I gjort hidtil? (Vores Thesis må ikke blive plagiat)
    - Problemformulering?
    - Fast Mødetid
* Uncanny Valley paper
  + 3 Groups of characters, non- reaslsitc, semi, realistic
  + Likert Scale
  + 1) Instructunal response
  + 2) Cognitive response
  + Event Related Potentials.
* EEG
  + CNNs
  + 1000 Hz
  + 32/24 Electorder
  + 100 Mia neuron
  + Hvor kommer signalet fra? Hvornpr signalet kommer!
  + Oversamplet i tid, undrsamplet i rum
  + 1D convulation over tid
  + Functional Conectivity
    - Correlations
  + Deep Learnings
    - Finding paraemters themselves
    - Epochs problem
    - Structur og dynamic samtidligt ☹
  + Attention
    - Subgate alignment
    - Subjective transformation
  + Repetation Similairty
    - Activations ud ag hidden layers
    - Hvilke data punkter ligner hinanden i hvilke modeller.
    - Samme representation af feattures, Temporal data and Spatial data.
  + Attention
    - Interpretability
    - Spatial and temporal attention
    - Transformer 🡪 Conformer
    - Catch embedding
  + Moter Imaging
    - Let at decoder
  + Emotion Recognition
  + Moabb -> Mother of all beachmark beachmark
* Papers
  + Central Alignment current
  + RankDeCode

Til næste gang

* Udkast til problemformulering til næste møde
* Læse papers
* Vælge emne

## Getting Aligned on Representation Similarity

* Join representation of all stimuli: Representation Dissimilarity Matrix
  + Cosine Similarity
  + Correlation Coefficient
  + Angle
* Systems
  + Embeddings with low signal-to-noise ratio
  + Two embedding functions
  + Two optionally learnable arrays of parameters.
  + Identity map?
  + Dis similarity quantifying
  + Similarity-quantifying: Spearman rank, cosine, Pearson
  + Dissimilarity-quantifying: Cross-entropy, cosine, contrastive representation learning
  + Descriptive: Dis-similarity and then measure alignment Representational Similarity Analysis, rank-correlation between RDM with Kendall’s tau, Pearson, symmetric
  + Differentiable, increase alignment of a model representation to another model or a brain region motivates the use of a differentiable alignment function. Error function or loss function. Minimize loss with gradient.
  + Representation fine-tuning,
    - Source parameter fixing (directional alignment)
    - Source parameter availability
    - Few-shot fine-tuning
    - Regularization
  + Symmetric from directional alignment
    - Symmtric alignment function over directional alignment functions
    - Symmetirc
      * Pearson, cosine, inner product
    - Directional, alignment in terms of one space
      * KL divergence
      * Embedding representations into probability distributions
  + Different measyres afford different inferences.
    - Accot asymmetric measures
  + Similarity Measure?
    - CKA (Centered Kernel Alignment)
      * Hilber-Scmidt Independence Criterion
      * 1-CKA
  + Open Problems & Challenges in Representational Alignment
    - RSA: Representational Similarity Analysis
    - Chosen systems and stimuli to compare
    - In a deep transformer which layer or components should we analyse?
    - EEG can distort or enhance features compared to the information tha is computationally available ot the underlying system.
    - Single-cell neural activity from cotical, which regions should we target?
  + Eliciting representations from blak-box systems
    - MCMC
      * Refined high-dimensional objects by acting as the rejection function in an MCMC sampling chain.
    - Serial Reproduction
      * Gibbs sampling algorithm
      * Modifyinh object dimensions by interaction with it using a computer slider
      * Diffusion processes
    - Measuring alignment
      * Euclidean distance metrics
    - Representational alignment help improve the alignment of behaviour?

Shared Representational Geometry Across NN

* Shared space inter-network RMS (iRSM)
* Space within-network (wRSM)
* (SRM) Shared Response Model
  + Rigid-body transformation
* Represnrtational Similarity Matrix
  + Linear vs rank correlation
  + 95 % bootstrapped Confidence Interval based on 50 simulation runs
  + Correlation between the average inter-network RSM and average withing-network RSM.

Similarity of Neural Network Representations Revisited

* Canonical Correlation Analysis (CCA)
* CKA can reliable identify correspondence between representations in networks
* Scalar similarity index
* One can first measure the similairity between every par of examples in each representations separately, and then compare the similarity structures
* Dot Product-Based Similarity:
* HSIC
  + Gretton, proposed statistic for determining whether two sets of variables are independtly. Converge 1/\sqrt(n), HISC= 0 implies independence. Noot an estimator of mutual information HSIC. Is equivalent to Maximum Mean Discrepancy between the joint distribution and the product of the marginal distributions.
* Centred Kernel Alignment:
  + CCA, Is Pearson's correlation in multple dimensions. U= XW\_x, Y= XW\_y and then W is weight vectors. Find W that maximize
  + SVCCA due to perturbation
  + Proejction Weighted CCA
  + Neuron Alignment Procedures

Questions:

* Paper: Shared Representational Geometry Across NN
  + What is Within-networks, inter-networks similarity?
  + Consistency?
  + Variance Explained
  + ConvNet
  + ResNet18
  + Data
  + Problem formulation
    - Spatial-Temporal
    - Spatial
    - Temporal

Ideas:

* Model on only Spatial, temporal and on both
* Metrics: CKA, CCA …
* Backup: Play around with neuron number inside layers.

PQ: How does representation similarity work across different models with regards to EEG signals in?